

Performing Structured Improvisations with pre-trained Deep Learning Models

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Abstract

The quality of outputs produced by deep generative models for music have seen a dramatic improvement in the last few years. However, most deep learning models perform in “offline” mode, with few restrictions on the processing time. Integrating these types of models into a live structured performance poses a challenge because of the necessity to respect the beat and harmony. Further, these deep models tend to be agnostic to the style of a performer, which often renders them impractical for live performance. In this paper we propose a system which enables the integration of out-of-the-box generative models by leveraging the musicians creativity and expertise.

Introduction

The popularity and quality of machine learning models has seen a tremendous growth over the last few years. *Generative models*, which are trained to produce outputs resembling a pre-specified data distribution, have attracted much attention from both the scientific and artistic community in large part due to the realism of the outputs produced. Of note are some of the Generative Adversarial Networks (Goodfellow et al., 2014) which have been able to yield high-quality images (Brock, Donahue, and Simonyan, 2019), image-to-image translations (Zhu et al., 2017; Wang et al., 2018), and even transfer of a professional dance performance onto an amateur dancer (Chan et al., 2018). The ability of these models to produce completely new outputs that are highly realistic has drawn a growing number of artists to incorporate them into their craft, taking steps into a new creative frontier.

In the musical domain, recent works produce music that is both realistic and interpolatable (Roberts et al., 2018), closely resembles human performance (Huang et al., 2019), and can aid in automatic composition¹. The increased realism of these models is typically accompanied with an increase in the amount of processing time required to generate outputs. If these outputs can be produced in an “offline” manner (i.e. generated well before they will be consumed) the longer processing times are not problematic. On the other hand, long processing times generally renders these

models inadequate for live performance. This issue is particularly stark in structured improvisation, such as in traditional jazz, where the music produced must respect the beat and harmony of the piece.

Despite the increased realism and consistency of the musical models mentioned above, the models are inherently *impersonal*: there is a single model for all users. Artists wishing to incorporate these models into their work are thus forced to either train their own model – requiring a good understanding of machine learning – or adapt their craft to the idiosyncrasies of the model – which can result in creative output that is not reflective of the artist’s style.

In this paper we introduce a software system that enables the incorporation of generative musical models into musical improvisation. This can be used as both a solo-performance or in an ensemble. Our system produces a performance that is a hybrid of human improvisation with melodies and rhythms generated by deep learning models. As we will describe below, our hybrid approach enables us to address the two aforementioned problems: real-time compatibility and stylistic personalization. It is worth specifying that our system does not require machine learning expertise.

The paper is structured as follows. We begin by providing some necessary background on recurrent neural networks and how they are used for rhythm and melody generation, followed by a discussion of related work incorporating machine learning models with artistic creation. We then present our system setup and describe the software backend in. Finally, we provide some empirical evidence of the efficacy of our system, followed by some concluding remarks and discussion of future avenues of research in.

Background

We use Recurrent Neural Networks (RNNs) (Rumelhart, Hinton, and Williams, 1986) as the machine learning models for generating drum beats and melodies. Recurrent Neural Networks are a special type of neural network which process a *sequence* of tokenized inputs one token at a time, updating an internal state after processing each input. This internal state can enable a type of “memory” for long-term dependencies. The network maintains a probability distribution over a finite dictionary of tokens; the model’s internal parameters determine the shape of the distribution conditional on its current internal state and the last token. During train-

¹<https://www.ampermusic.com/>

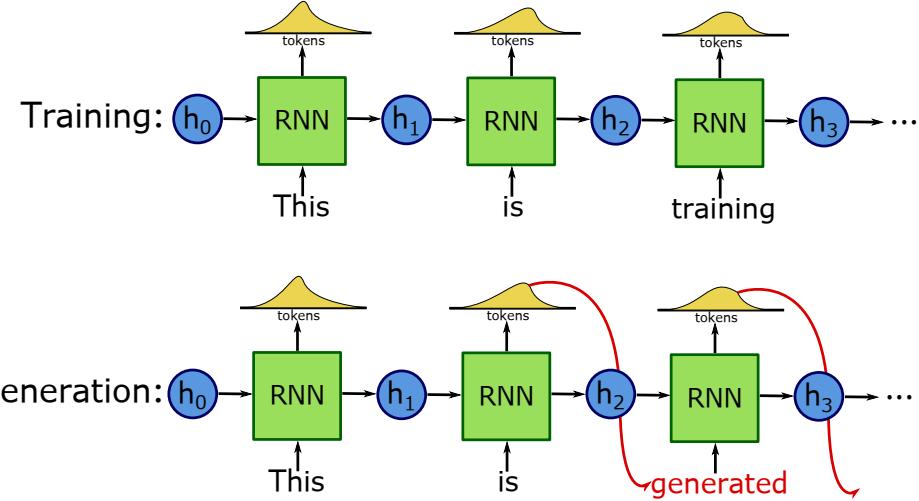


Figure 1: An RNN being trained on English sentences. The green squares represent the RNN, where we are explicitly illustrating the updating internal states h_i as blue circles. The output of the model is a distribution over tokens (in yellow). The top frame shows an example of a training pass through the sentence “This is training ...”. The bottom frame shows how the model can be used for generation when fed in the primer sequence “This is”. In this example, the sample from the model’s distribution over tokens is ‘generated’.

ing, the internal model parameters are updated so as to maximize the probability mass assigned by the network to the true token t_{n+1} , given the previous tokens $t_{1:n}$. One of the most popular types of RNN are the Long Short-Term Memory networks introduced by Hochreiter and Schmidhuber (1997).

A trained RNN can be used for generation: after processing a sequence of tokens $t_{1:n}$, sample from the resulting internal distribution over the token dictionary. A properly trained model will produce outputs that have a high likelihood to have come from the distribution of the training dataset. When using these models for generation, we will refer to the initial sequence $t_{1:n}$ fed into the model as the *primer sequence*. Figure 1 illustrates this process for an RNN where the tokens are English words.

We will make use of two LSTM-models from Google Magenta. The first is MelodyRNN (Magenta, 2016b). It processes *note events* as tokens, where a note event contains a note’s pitch and its duration. The model assumes monophonic melodies (i.e. only one note played at a time) and is instrument agnostic. Thousands of MIDI files were used for training. These MIDI files were quantized into 16th notes: that is, the minimum allowable time between two notes are one 16th note². The Magenta team provides a few models trained with different configurations, but we use the *Attention* configuration in this work, as we found it produces the best results. When using this model to generate new melodies, the melodies produced tend to match the key signature and note density of the primer melody sequence fed into it, which is a desirable property for our use case.

The second is DrumsRNN (Magenta, 2016a). The model is similar to MelodyRNN, but here there is polyphony

as multiple drums can be hit simultaneously. As for MelodyRNN, this model was trained on thousands of MIDI files, quantized into 16th notes.

Related Work

The use of deep learning models for creative purposes has witnessed a steady increase in the artistic and scientific community in the past few years. Arguably the most common approach is to train a custom model on a particular dataset to produce outputs which are novel, but match the distribution of the training set. A representative example in the visual domain is the Pix2PixHD model (Wang et al., 2018) trained on a corpus of Balenciaga runway shows to produce new “imagined” outfits (bar, 2018). Mathewson and Mirowski (2017) and Mathewson et al. (2019) explore methods for integrating generative language models with improvised theatre.

In the musical domain, there is a rather stark difference when comparing the outputs of deep-learning models against “shallow” models. We begin our survey of related work with those that came before the deep-learning revolution, and then proceed to some works using deep models.

There have been a number of works proposing new types of digital instruments which make use of machine learning models. The Wekinator (Fiebrink, 2009) enables users to train new models in a *supervised* fashion by providing pairs of inputs and expected outputs; inputs can be provided in many forms including using computer controllers and physical gestures, while outputs can be sent to any musical, digital or physical actuator. This contrasts with our proposed framework, which does not require retraining a model, but rather adapt the outputs of a pre-trained deep learning model to a performer’s style.

Thom (2000) and Thom (2001) build probabilistic models

²There are sixteen 16th notes in one bar of 4/4 time.

to emulate an improviser’s tonal and melodic trends. Johnson, Keller, and Weintraut (2017) makes use of two LSTMs: one for intervals between notes and the other for note intervals relative to the underlying chord progression; these trained models are then combined to generate melodies in a recurrent note-by-note fashion.

In (Weinberg et al., 2009) the authors introduce *shimon*, a robot marimba player capable of interacting with human players. The robot has human-like movements (such as head-bobbing, “gazing” to pass on the solo to another player, etc.) which make it natural to interact with.

Closely related to our use of ‘continuations’ are *The Continuator* of Pachet (2003), where the authors use Markov models to adapt to a user’s style. In contrast to our work, however, the continuator is agnostic to the underlying beat of a performance, which is essential to jazz improvisation.

Bretan et al. (2017) propose training a deep autoencoder to encode melodies played by a performer into a latent space that has been trained to capture musical consistency; the closest melody from a library that has been embedded into the same latent space is returned, allowing their system to respond in near real-time. Although the authors augment the original library (a large corpus of MIDI files) by “humanizing” the samples via application of temporal shifts, the outputs are still limited to what is available in the library. Thus, the resulting *style* is more reflective of the augmented library than of the human performer.

Roberts et al. (2018) propose a deep autoencoder model for encoding melodies into a latent space, combined with a deep decoder for converting points from that latent space into cohesive melodies.

Huang et al. (2019) trained a transformer model (Vaswani et al., 2017) on a dataset of virtuoso piano performances, resulting in a model that can produce highly realistic and novel musical snippets³.

More recently, a number of creative web applications combine some of the deep-learning models mentioned above with interactive interfaces that allow users with no musical training to create music (Parviainen, 2018; Dinculescu, 2018). Hantrakul and Kondak (2018) use an RNN to convert gestures on a Roli Lightpad into sound.

These digital instruments, however, tend to operate in isolation; specifically, they prescribe the beat and harmony (or are agnostic to it), rather than conforming to pre-existing beats and harmonies. In jazz performance, especially when performing with other musicians, respecting these is crucial when improvising⁴. In this work we propose a system enabling the integration of out-of-the-box deep generative models for this type of performance.

System setup

Our setup assumes a piano keyboard connected to a computer via MIDI used for input, along with an additional controller for enabling more MIDI control messages; in our case

³See <https://magenta.tensorflow.org/music-transformer> for some examples.

⁴We are excluding free jazz here, which allows for more flexibility in performance.

we are using the Korg Nanokontrol2 MIDI controller but the system can be used with any MIDI controller. We use SuperCollider⁵ to detect all incoming MIDI events and pipe them as OSC⁶ messages to a Python backend running on the same machine. The Python backend processes the notes and may then send an OSC message containing notes to be played to SuperCollider, which either generates the sound or forwards them to an external MIDI controller for producing the sound. Figure 2 illustrates the main components of our system.

The SuperCollider component acts mostly as a bridge between the MIDI controllers and the Python backend. It defines a set of handlers for routing MIDI input messages to the backend via OSC messages, and handles OSC messages from the backend. When a note on/off message is received from the backend, it can either redirect to an external MIDI controller or produce the sound itself. For the latter, the SuperCollider code loads a set of WAV files as well as a few synthetic instruments for playback.

Backend design

At its core, the Python backend is running a continuous loop over a customizable number of bars, each with a customizable number of beats. Each is discretized into 16th note segments (so one bar in 4/4 time signature will have 16 intervals). Multi-threading is used to allow for real-time response, and we maintain a set of global variables that are shared across the different threads, the most important of which are listed below:

- **time_signature**: An object containing a pair of integers denoting the *numerator* (4, 6, 7, etc.) and *denominator* (4, 8, or 16) of the time signature.
- **qpm**: A float indicating the speed (quarters-per-minute) of playback. One quarter note is equal to four 16th notes, so this value indicates the time needed to process four 16th note events.
- **playable_notes**: A SortedList where we store each playable note event. Each element contains the type of playback event (click track, bass, drums, etc.), the note pitch, the instrument itself (bass, keyboard, hi-hat, bass drum, crash, etc.), and the 16th note in the bar where the event occurs.
- **bass_line**: Similar to *playable_notes* but containing only the current bassline.
- **accumulated_primer_melody**: A list which will accumulate the note pitches played by the human improviser. Once enough notes have been accumulated they will be sent as a ‘primer’ melody to MelodyRNN. This is discussed in more detail in the Improvisation section.
- **generated_melody**: A list containing the note pitches produced by MelodyRNN. When full, the note pitches played by the human will be replaced by the pitches in this buffer.

Our open source-code can be accessed at <https://github.com/psc-g/Psc2>.

⁵<https://supercollider.github.io/>

⁶<http://opensoundcontrol.org/>

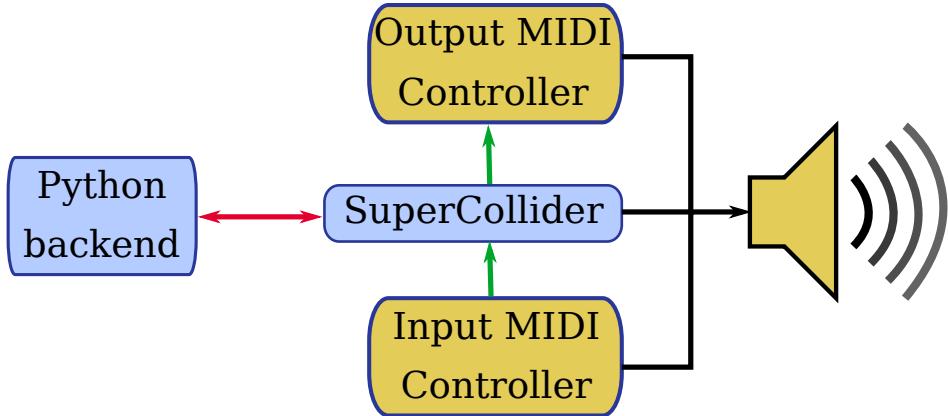


Figure 2: The main components of our system. Orange and blue boxes indicate hardware and software components, respectively. Black arrows indicate raw audio signals, green arrows indicate MIDI signals, and red arrows indicate OSC signals.

Click-track generation

The first step is setting the number of bars, time signature, and tempo (qpm). The user may change the number of bars, time signature numerator, and time signature denominator via a set of buttons on the Nanokontrol2. The qpm may be adjusted via a knob or by tapping the beat on a button. These define the length and structure of the *sequence*, which the system will loop over. Once these are set the user may start playback by hitting the ‘play’ button on the Nanokontrol2. This will start a click-track which will make use of 3 different click sounds:

1. The first will play on the first beat of the first bar, to indicate the start of the sequence. This is important for the user to know the start of the sequence when recording a bassline or chords.
2. The second will play on the first beat of the remaining bars in the sequence (if at least two bars were selected)
3. The third will play within each bar at a frequency marked by the time signature denominator: if the denominator is 4, it will play a click every four 16th notes; if it is 8, it will play every two 16th notes; if it is 16 it will play a click every 16th note.

Once the click-track has been started, the user can place the system in one of four *modes* via buttons on the Nanokontrol2. When SuperCollider is in charge of producing sounds, each mode uses a different instrument for playback.

- **bass:** The user can record a bassline which will be looped over. After entering this mode, recording begins as soon as a note is pressed and proceeds until the end of the sequence is reached.
- **chords:** The user can play a set of chords to include in the loop playback. As in bass mode, recording begins as soon as a note is pressed and proceeds until the end of the sequence is reached.
- **improv:** Used for improvising over the loop playback in a call-and-response between the human and the machine learning model. This mechanism is discussed in more detail in the Improvisation section.

- **free:** Free-play mode, where the human can improvise freely over the loop playback.

Drums generation

Our system generates two types of drum beats: a deterministic one and another which is generated by a machine learning model. The deterministic one is built off of the bassline as follows:

1. A bass drum note is added at the first beat of every bar.
2. A snare note is added at each bass note onset.
3. Hi-hat notes are added at each 8th note (so every two 16th notes).

By pressing one of the Nanokontrol2 buttons, this deterministic drum beat is fed into DrumsRNN as a ‘primer’ to produce a new beat. Figure 3 illustrates this process in musical notation.

Improvisation

The improvisational part of our system is inspired on the call-and-response improvisations that are common in traditional jazz. In these sections two or more musicians take turns improvising over the same piece, and each musician usually incorporates melodies and/or rhythms played by previous musicians into their improvisations.

There are two main components to an improvisation: the pitches chosen and the rhythm of the notes. In our experience playing with generative models, such as MelodyRNN, we found that the rhythm of the melodies produced is not very reflective of the types of rhythms observed from professional improvisers. This may be due in large part to the 16th note quantization that is necessary for training the models. To overcome this issue, we propose a hybrid approach: the machine learning models provide the pitches, while the human provides the rhythm.

The way this is achieved is as follows:

1. Collect the pitches played by the human improviser in the *accumulated_primer_melody* global buffer.

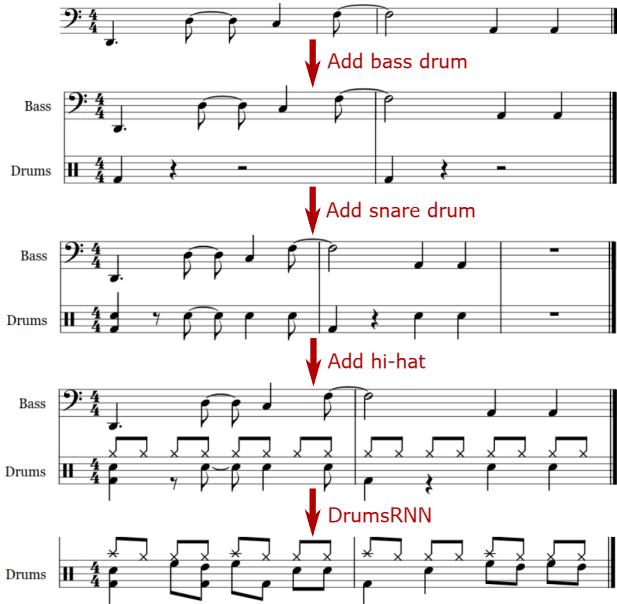


Figure 3: Building the drum beats. From top-to-bottom: starting from a specified bassline, bass drum notes are added on the first beat of each bar, snare drum notes are added for each bass-note onset, and finally hi-hat notes are added at each 8th note. This deterministic drum beat can then be sent as a ‘primer’ to DrumsRNN which will generate a new beat.

2. Once the number of notes in the buffer is above a pre-specified threshold, the buffer is fed into MelodyRNN as a primer melody in a separate thread.
3. When the MelodyRNN thread has finished generating a new melody, it will store *only the pitches* in the *generated_melody* buffer (the rhythmic information is dropped).
4. When the main looper thread detects that the *generated_melody* buffer has been filled, it will **intercept** incoming notes played by the user and replace their *pitches* with the pitches stored in *generated_melody* (and removing said pitch from the buffer). Figure 4 illustrates this process.
5. Once *generated_melody* is empty, return to step 1.

Our hybrid approach to machine-learning based improvisation allows us to mitigate the two problems mentioned in the introduction: real-time compatibility and stylistic personalization. The former is handled by performing the inference in a separate thread and only using it when it is available. The latter is handled by maintaining the rhythmic inputs from the human performer. It has been found that rhythm can significantly aid in facilitating melody detection (Jones, 1987), which we believe also carries over to enhancing the personalized style of performance. Further, by leveraging the human’s rhythmic input, we are able to avoid having the limitation of the 16th-note quantization that the RNN models require.

We provide some videos demonstrating the

use of this system at <https://github.com/psc/Psc2/tree/master/research/nips2018>.

Evaluation

I have used this system for live jazz performance in a piano-drums duet. The songs performed were some that I regularly perform with my trio (www.psctrio.com), and the system was engaged during the improvisation sections of these songs. Since there was a human drummer performing, only the improvisation (MelodyRNN) part of our system was used. Some of my thoughts from these performances are listed below.

Strengths

- The system was able to respond in real-time: there was no noticeable lag between playing a note on the piano and hearing the resulting sound.
- Since the system produces MIDI outputs, I could use any desired sound from my analogue synthesizer, which made for a more organic sound.
- The audience (many of which are familiarized with my style) reported not noticing that there was an external system affecting the improvisations (they were only made aware of it after the show). I take this as a very successful signal, as it demonstrates that this approach is able to maintain the key stylistic elements of the human performer.
- I did find that I had to adjust my improvisations to account for the element of uncertainty that the system introduced. Specifically, not knowing which pitches would be produced from they key-presses forced me away from my go-to lines and into a new creative space.

Weaknesses

- I found it difficult to use the system in songs with many harmonic shifts. Since we did not impose boundaries for recording the human performer’s notes (such as at the start and end of a jazz chorus), the times when the system would begin replacing the human’s notes were somewhat arbitrary, possibly resulting in melodies that are not properly aligned with the underlying harmony. On *modal* songs (where the harmony does not shift) I had no issues.
- Sometimes the system would come in at the “wrong” time; specifically, when I was in the middle of a line that was cut short, resulting in an awkward melody.
- If I was at one register of the piano when the system began recording my notes and ended up in a different register right before the system engaged, when the MelodyRNN notes began replacing mine, they would tend to start in the first register, causing a big jump in pitch. This is generally discouraged from a musical perspective, which forced me to improvise mostly within two octaves.

Conclusion and Future Work

In this paper we have introduced a system that enables the integration of out-of-the-box deep learning models for live

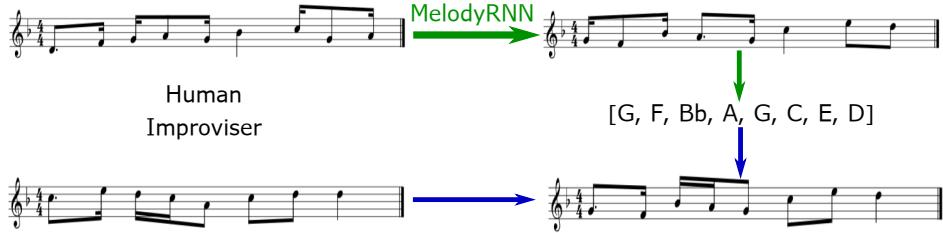


Figure 4: Building the hybrid improvisation. 1. The melody from the human improviser (top-left) is fed into MelodyRNN. 2. MelodyRNN produces a new melody (top-right). 3. The human improviser plays a new melody (bottom-left). 4. A new hybrid melody is created by combining the pitches from the MelodyRNN model with the rhythm from the most recent human improvisation (bottom-right).

improvisation. We have designed it in a way that it does not require machine learning expertise to use, and can be extended to other types of musical generative models with little effort. Our hybrid approach for generating machine-learning based improvisations maintains the style of the human improviser while producing novel improvised melodies.

Although our system was built with MelodyRNN and DrumsRNN, the setup can be used with any musical generative model with relatively little effort. Along these lines, one avenue we would like to explore in the future is the incorporation of models which do not require quantization, such as PerformanceRNN (Simon and Oore, 2017); one challenge is to ensure that the personal style of the human improviser is maintained.

Expert musicians are able to produce high-quality improvisations *consistently* from having honed their craft over many years of practice. A common frustration with these artists, however, is that they often find their improvisations too predictable, and struggle escaping their “pocket”. Our hope is that systems like the one we are proposing here can push expert musicians, and artists in general, out of their comfort zone and in new directions they may not have chosen to go to on their own. The experience of the pianist we reported in the previous section perfectly showcases this.

We hope to improve the system by allowing the performer to have more control over when the system begins recording, and when the system replaces the notes. We have already begun experimenting with this extra modality using a MIDI footpedal. Initial experiments suggest this added level of control mitigates for many of the issues raised by the human performer regarding the timing of when the system is engaged, while maintaining the novelty of the melodies produced.

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